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Solution of Combined Heat and Power Economic Dispatch Problem Using Genetic Algorithm

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Abstract

This research proposes a synergistic meta-heuristic algorithm for solving the extreme operational complications of combined heat and power economic dispatch problem towards the advantageous economic outcomes on the cost of generation. The combined heat and power (CHP) is a system that provides electricity and thermal energy concurrently. For its extraordinary efficiency and significant emission reduction, it is considered a promising energy prospect. The broad application of combined heat and power units requires the joint dispatch of power and heating systems, in which the modelling of combined heat and power units plays a vital role. The present research employs the genetic optimization algorithm to evaluate the cost function, heat and power dispatch values encountered in a system with simple cycle cogeneration unit and quadratic cost function. The system was first modeled to determine the various parameters of combined heat and power units towards solving its economic dispatch problem directly. In order for modelling to be done, a general structure of combined heat and power must be defined. The test system considered consists of four units: two conventional power units, one combined heat and power unit and one heat-only unit. The algorithm was applied to test system while taking into account the power and heat units, bounds of the units and feasible operation region of cogeneration unit. Output decision variables of 4-unit test systems plus cost function from Genetic Algorithm (GA), was determined using appropriate codes. The proposed algorithm produced a well spread and diverse optimal solution and also converged reasonably to the actual optimal solution in 51 iterations. The result

obtained compared favourably with that obtained with the direct solution algorithm discussed in a previous paper. We conclude that the genetic algorithm is quite efficient in dealing with non-convex and constrained combined heat and power economic dispatch problem.

Keywords

Optimization, Power and Heat Constraints, Generator Limits, Genetic Algorithm, Convergence

1. Introduction

Economic dispatch is basically concerned with the problem of determining the outputs of the generating units in service. The objective is to meet up with the total load demand while keeping the fuel cost at the barest minimum. Economic dispatch (ED) problems aim principally at computing the optimal schedule of online generating units to satisfy power demands at the least operating cost. The system and operating constraints necessary for this task are ramp rate limits [1]; and forbidden zones. The latter is a nonlinear characteristic of a machine due to distortion of magnetic field controlled by the power angle, the armature and excited currents respectively [2]. The fuel cost function of each generating unit is approximately represented by a quadratic cost function. Economic dispatch (ED) problems represent an important industrial class of optimization problems considered particularly difficult for conventional optimization techniques. The main problem in economic dispatch lies with the distribution of generator load to produce the measure of electricity required. Examples of economic dispatch problems could be economic load dispatch in the operation of power systems, dynamic or static dispatch, hydrothermal scheduling problems and others [3]. A significant amount of decision variables and non-linearity, ordinarily characterize Economic Load Dispatch problems (ELD), including non-linear constraints due to the characteristics of modern units. Improvements in solving this class of optimization problems have led to significant savings in costs. The emergence of modern computational intelligence algorithms—Genetic algorithms, Differential Evolution algorithm, Artificial Bee Colony algorithms, Whale Optimization algorithm, Kho-Kho optimization algorithm etc., has paved the way for solutions to complex optimization problems. Genetic algorithm, based on principle of genetics and natural selection, provides positive results when deployed to certain optimization problems. The constraint optimization problem encountered in this research while not considering any additional knowledge about the problems at hand is an instance.

We begin with a brief overview and description of economic dispatch is provided in Section 3. Section 4 is the formulation of combined heat and power economic dispatch problem; Section 5 anatomized combined heat and power unit (Cogeneration unit); and lastly, Section 6 reviewed genetic algorithm for com-

bined heat and power Economic dispatch (CHPED) problem. In Section 7, we discussed the GA results. Finally, conclusions resulting from the study are given in Section 8.

2. Brief Literature

Evolutionary algorithms include Genetic Algorithms (GA) [3], Evolutionary Programming (EP) and Differential Evolution (DE) [4]. Another popular class of algorithms is Swarm Intelligence algorithms [5] [6] [7]. Although these techniques can deliver an assurance of finding global optimum, the potency of genetic algorithm is demonstrated using its codes. During such demonstration, it was found that genetic algorithm can find better solutions in terms of objective function value, convergence speed and number solutions in comparison with other evolutionary and meta-heuristic algorithms. The above reasons have accorded genetic algorithm a remarkable attention span, compared with other optimization algorithms. The traditional form of energy system is restricted to a single electric/thermal energy source wherein the interaction and reciprocal advantages between varied energy sources cannot be fully utilized. A single form of energy can no longer guarantee green and systematic energy demand [8]. Hence, it is vital to map out a secure and inexpensive integration of heat and power system. The CHP system or cogeneration assemble heat and electricity gained from a single energy source has a high-level efficiency compared with a single power generation system, since the heat from the power generation can be further reused. In today's energy system, as well as the concerns of carbon emissions believed to make a significant contribution to the global climate change, combined heat and power systems are preferable [9]. Combined heat and power systems can also provide an economic advantage since such systems will lead to a reduction in fuel use and greenhouse gas emissions that in turn lead to certain tax exemptions and in many places receive incentives from governments [10]. A significant amount of research articles has in recent times been invested as proof to the vital benefits of the systems. Each literature has helped in gaining a better understanding as well as the optimization of the systems' operations. In Comparison to laboratory-based scale research, case studies for real life combined heat and power systems provide more accurate results and insight into the systems' characteristics and their optimization options. Case studies from past researches at different global locations [11] suggest the importance of running the prime mover, usually an engine at its maximal efficiency to obtain cogeneration benefits. It also suggests that sizing the engine correctly according to demand is very important. The same suggestion holds that a properly constructed combined heat and power (CHP) system can certainly foster cost minimization, thereby guarantying a return on investment. Emissions from combined heat and power (CHP) system have also been investigated in comparison with coal-fired power station or natural gas powered boilers and other systems [12]. The results suggested a considerable reduction of all the emissions regardless of the original

system. The objective of this research is to minimize input fuel cost while maintaining bounds of the units and feasible operating region of the cogeneration unit alongside power and heat constraints. Our approach is to use genetic algorithm in the evaluation of combined heat and power economic dispatch.

3. Methodology

The proposed problem is basically on Economic dispatch (ED), which is a constraint optimization problem whose objective is to find the most cost-efficient schedule of a generating unit while maintaining the operational constraints and load demand. It is obvious that at optimum point, all units (excluding those at their limit) would be operating at equal incremental costs. To achieve economic operation of generating units in a plant, economic dispatch is carried out. ED problem is one of the vital issues in power system operation and is commonly formulated as an optimization problem Hatziargyriou *et al.* [12]. It involves active power allocations among power generators to minimize overall operating cost by maintaining power and heat balance constraints and other operational constraints Wen *et al.* [13]. Numerous conventional methods have been established to solve the Economic Dispatch, for example the λ-iteration method, Lin *et al.* [14], the Lagrangian relaxation method Guo *et al.* [15], quadratic programming, Fan and Zhang [16], the improved particle swarm optimization Chiang [17], differential evolution algorithm etc. However, all these optimization algorithms are implemented in a centralizedform requiring central nodes to collect global information on all the generators, Guo *et al.* [18] and transmit command globally. In practice, collecting detailed information is usually costly in both communication and computation especially when the power system becomes more complex as explained in Pourbabak *et al.* [19]. Besides, such centralized algorithms are unable to meet the plug-and-play requirements in the newly smart grid system.

4. Formation of CHPED Problem

Combined heat and power Economic dispatch problem is a constraint optimization problem consisting of objective function, linear and nonlinear equality and inequality operational constraints. The objective function indicates the contribution of each decision variables to the function to be optimized in the optimization problem. The objective function also represents the input fuel cost while the constraints could be inequality or equality constraints that match load and heat demands with power generation [20]. In this research, system transmission losses are neglected, leaving load, heat demand, and nonlinear equality and inequality constraints as the only available Constraints. The test system comprises four units: two conventional Power units, one co-generation or combined unit and a heat-only unit. The CHPED problem is to determine the optimal power and heat output decision variables while maintaining the system constraints. The cost function is minimized by deploying Genetic Algorithm.

4.1. Objective Function

Objective function is a mathematical term that describes how different decision variables contribute to a certain value that is sought to be optimized. The goal of economic dispatch is to decrease fuel input cost by satisfying the constraint of all the units (Power and Heat constraints) and other operational constraints. By this we mean that at low power and heat demands, each unit has to operate at minimum power and heat bounds (limits) [21]. For k unit system, the total fuel cost (TFC) is used as the cost or objective function for economic dispatch. The objective function of the combined heat and power economic dispatch problem is modeled as follows:

$$\text{Min } C = \sum_{i \in e} c_{e,i}(p_i) + \sum_{j \in c} c_{c,j}(p_j, q_j) + \sum_{k \in h} c_{h,k}(q_k) \tag{1}$$

h and p are the heat and electrical power output of respective units:. $c_{e,i}(p_i)$, $c_{c,j}(p_j, q_j)$ and $c_{h,k}(q_k)$ constitute the fuel cost function of ith power-only unit, fuel cost function of jth cogeneration unit and fuel cost function of kth heat-only unit, respectively. Given the quadratic fuel cost function of power-only units in Naira we have:

$$c_{e,i}(p_i) = \alpha_i + \beta_i p_i + \gamma_i p_i^2 \tag{2}$$

where, α_i, β_i and γ_i are the cost coefficients of ith power-only unit, the production cost of cogeneration and heat-only units are given in Equations (3) and (4).

$$c_{c,j}(p_j, q_j) = \alpha_j + \beta_j p_j + \gamma_j p_j^2 + \delta_j q_j + \varepsilon_j q_j^2 + \zeta_j p_j q_j \tag{3}$$

$$c_{h,k}(q_k) = \alpha_k + \delta_k q_k + \varepsilon_k q_k^2 \tag{4}$$

where, $\alpha_j, \beta_j, \gamma_j, \delta_j, \varepsilon_j$ and ζ_j are the cost coefficients for the jth cogeneration unit, α_k, δ_k and ε_k represent the coefficients of kth heat-only unit. The objective function of the CHPED problem is to be minimized total cost of serving the heat and power demand subject to equality and inequality constraints.

4.2. Equality Constraints; Heat and Power Balance Constraints

Real power created by power unit plus the real power generated by cogeneration unit is equivalent to the real power demand of power systems neglecting power loss, and this is modeled mathematically in Equation (5) below:

$$\sum_{i \in e} p_i + \sum_{j \in c} p_j = P^D \tag{5}$$

Comparably, the total heat generated by boilers plus the active heat generated by cogeneration unit is equal to the heat demand neglecting heat loss and is modeled using Equation (6):

$$\sum_{j \in c} q_j + \sum_{k \in h} q_k = Q^D \tag{6}$$

where P^D and Q^D are the total heat and power demand of system respectively. In the heat equality constraint, heat losses are postulated to be zero because no research work about heat losses during process of transmitting heat to

heat loads has been carried out [22]. For clarity, that postulation was employed in this research. Therefore, heat losses are negligible. Furthermore, if heat losses are a function of heat outputs similar to power loss function, the Karush-Kuhn-Tucker (KKT) Lagrange multiplier for the dispatch problem given is

$$
\begin{aligned}
L &= \left(\alpha_i + \beta_i p_i + \gamma_i p_i^2\right) + \left(\alpha_j + \beta_j p_j + \gamma_j p_j^2 + \delta_j q_j + \varepsilon_j q_j^2 + \zeta_j p_j q_j\right) \\
&\quad + \left(\alpha_k + \delta_k q_k + \varepsilon_k q_k^2\right) - \lambda_p \left(\sum_{i \in e} p_i + \sum_{j \in c} p_j - P^D\right) - \lambda_p \left(\sum_{j \in e} q_i + \sum_{k \in h} q_j - Q^D\right)
\end{aligned}
\tag{7}
$$

4.3. Inequality Constraints; The Capacity Limits Constraints

The inequality constraints for the above problem are given as:

$$
p_i^{\min} \leq p_i \leq p_i^{\max}
\tag{8}
$$

$$
a_{ij} * p_i + b_{ij} * q_i \geq c_{ji}, \quad j = 1, \cdots, n_i
\tag{9}
$$

$$
q_k^{\min} \leq q_k \leq q_k^{\max}
\tag{10}
$$

where, $p_i^{\min}$ and $p_i^{\max}$ represent the minimum and maximum power outputs of ith power plant units in MW, the output of the jth cogeneration unit is presumed to lie in a region in the P_i-Q_i plane bounded by n_i lines, $q_k^{\min}$; and $q_k^{\max}$ are the minimum and maximum heat output of the kth heat-only unit. The power production limits of combined heat and power unit are dependent to the unit heat production and vice versa [23]. The heat-power Feasible Operation Region (FOR) of a combined heat and power unit is illustrated in **Figure 1** below. Note that the lower and upper bounds of heat-only and power-only units are constricted by their own generation limits.

4.4. Data Set for the New CHP Dispatch Problem

Table 1. Power units-cost.

Units	$PG_{\max}$	$PG_{\min}$	α	β	γ
1	250	10	1000	13.5	0.0345
2	200	20	1245	13.1	0.033

Table 2. (Unit 3) cogeneration unit-cost coefficients.

Units	α	β	γ	δ	ε	ζ
1	2650	14.5	0.0345	4.2	0.03	0.011

Table 3. (Unit 4) heat unit cost coefficients.

Units	α	δ	ε	$Q_{\max}$	$Q_{\min}$
1	1200	4.2	0.02	250	20

Table 4. Coordinate of the corners of the feasible regions of co-generation units.

Corners	(p_1, q_1)	(p_2, q_2)	(p_3, q_3)	(p_4, q_4)
Unit 3	(20, 0.1)	(200, 0.5)	(195, 120)	(15, 110)

4.5. Combined Heat and Power Generation (CHP)

Cogeneration is a system that provides electricity and thermal energy concurrently. It consists of a generator, a heat recovery system and electrical interconnections. The thermal power is constructively reprocessed from the heat secured from combustion in the prime mover of the system. Cogeneration systems application increases the effectiveness of energy production from 35% up-to 85%. This economic viability has propelled people to install the systems, knowing that the production of electricity and heat is on site. Recent researches on cogeneration have concentrated on novel configurations of cogeneration plants using fuel as source energy [24] [25]. The increasingly severe requirements for carbon IV oxide, Sulphur dioxide (SO_2), Nitrogen Oxides (NO_x) and other greenhouse gases reduction led to a more universal promotion of distributed energy systems. One of the most effective methods facing the energy saving challenges happens to be the use of cogeneration systems. Furthermore, combined heat and power (CHP) generation is significantly more methodical than the distinct production of heat and power because of its reduction of overall fuel utilization which leads to low emission of greenhouse gases [26]. These greenhouse gases pollute the air in the environment, generate acid rain, and are also the major contributors to global warming. To obtain optimal utilization of combined heat and power units, combined heat and power is integrated into Economic dispatch problem to form the combined heat and power economic dispatch as an optimization problem. Cogeneration units have power and heat outputs which show that the operating orbit of cogeneration plants is more complex than either a heat only or power only unit. The recent shift shows that combined heat and power is one of the techniques to decentralize energy. It does not only ensure minimal loss on transmission system, but also boosts the system's competence while also providing energy either directly or near to end users. For effective application of cogeneration units, the economic dispatch of combined heat and power was established. The fundamental objective of the combined heat and power economic dispatch is to evaluate the most economic loading points of the combined heat and power generation units such that both heat and power demands are utilized within the bounded region in the heat versus power dimensional surface.

5. Feasible Operating Region for CHP Units

The feasible operating region (FOR) of a cogeneration unit includes both heat and power demand for which both are functions of each other. Figure 1, the enclosed area of the quadrilateral ABCD indicates the feasible operation region of the combined heat and power unit of this research paper. At point O—feasible region—the unit is not bounded by any constraints hence, the operating point is positive. For a point to be feasible it should be above line AB, below line CD, right of AD and left of BC and anything contrary to these is infeasible operating region. Output decision variables of cogeneration unit could be inside, on the line segment or outside the polyhedron. When output decision variable is on the
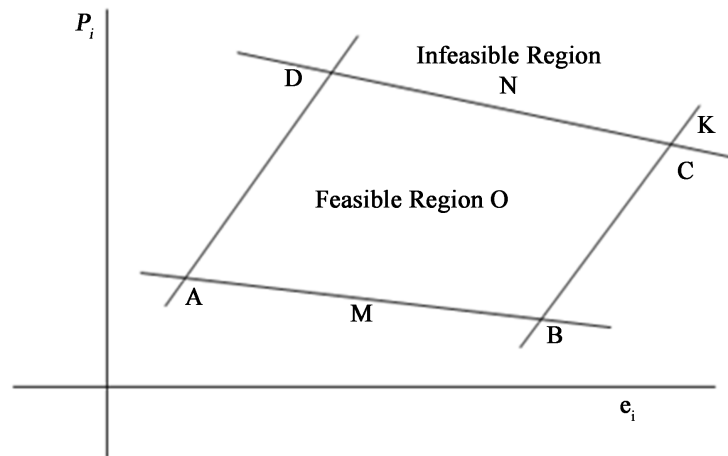
Figure 1. Feasible operation region of a cogeneration (CHP) unit.

line segment, its value is zero. It is however negative when output is neither inside nor on the line segment of polyhedron that is outside the polyhedron. Power generation limits of CHP units are specified by combined functions incorporating the unit's heat generation, and vice versa. The closed area surrounded by the curve ABCD indicates the feasible region of the cogeneration units.

Generator Limits

The dispatch gained based on the lambdas computed using equations may sometimes not be as feasible. The reason being the capacity constraints have not been taken into account in deriving this relation. The basic idea in handling these constraints is to identify the units that violate the constraints and set the violating quantities at their appropriate limit. The system demand is modified to reflect the fact that their outputs are fixed and known.

6. Genetic Algorithm (GA)

Various techniques have recently been proposed for solving the multimodal optimization problems. They can be divided into two main categories: deterministic and stochastic (meta-heuristic) methods. Deterministic methods, for example: gradient descent method or quasi Newton method, when they solve complex multimodal optimization problems, may easily get trapped in some local optimum as a result of deficiency in exploiting local information. They depend mainly on a-priori information about the objective function which can lead to fewer reliable results. Stochastic algorithms on the other hand combine randomness as well as rules mimicking several phenomena. These phenomena include physical processes—simulated annealing proposed by Kirkpatrick [27]; evolutionary processes—evolutionary algorithm put forward by Koza [28], de Jong [29], and Fogel [30]; genetic algorithms (GAs) suggested by Goldberg [31] and Holland [32]); and immunological systems (e.g. Artificial immune systems put forward by de Castro [33]); electromagnetism-like (put forward by Birbil [34]) and gravitational search algorithm (put forward by Rashedi [35]). Darwin's

theory of biological evolution as an optimization technique birthed Genetic algorithms. Its principal objective is obtained from natural evolution, hence, biological operators such as crossover, mutation and selection play significant role in Genetic Algorithms. Genetic algorithm has three randomly created phases: original population of chromosomes, crossover operator and mutation operator [36]. Respective chromosomes constitute unique solution to the problem and its quality is determined by the value of fitness function. Genetic algorithm commences by creating some random solutions denoted as the initial population. In the next phase, random crossovers give rise to a new successor and in step three; with random value of mutation a few of genes in chromosome are adjusted or replaced. The new generation of solutions is then used in the next iteration of the algorithm. Traditional GAs usually function well for unique optimum problems but unsuccessful if they have to find multiple solutions. However, GA coincides often with a local optimum after a certain number of generations. This is due to a low variety in the population or by the incapacity of the mutation process to avoid local optima.

6.1. Five Components for the Sequential Execution of Genetic Algorithm

- A worthy genetic representation for individual (chromosomes).
- A technique to create the initial population.
- A fitness function to calculate the quality of each potential solution.
- Genetic operators that adjust the genetic configuration of parents to produce a new offspring.
- The choice of the values of the various genetic algorithm parameters (population size, cross over rate, mutation rate, stopping criteria... etc.)

6.2. Genetic Operators Initial Population

As genetic algorithm begins its search process for the optimal solution by acting on the initial population which is a set of potential candidates, the initialization method is a very important step since it alters the efficiency of the genetic algorithm. Hence, the choice of an efficient initial population method enhances the genetic algorithm's search effectiveness. The initial population is usually created randomly in the standard genetic algorithm. However, the use of a random process causes invalid solutions which increase the algorithm's convergence time. Thus, coupled with proposing new constructive methods that permit only valid solutions in the initial population, researchers have also used a combination of random and constructive methods to construct the initial population of genetic algorithm. Population size is a generally fixed parameter during genetic algorithm execution. But there are modified versions of genetic algorithm where the size is dynamic. The choice of the value of this parameter is an influential factor for determining the quality of genetic algorithm convergence [37]. In this research, a random approach was used for creation of initial population with a fixed population size throughout the algorithm execution. This is because the

generated solution satisfied the underlying constraints (power and heat) of the combined heat and power problem. It explored the operating bounds and then generated several feasible solutions capable of constituting the initial population of genetic algorithm.

6.3. Fitness Function

Once the initial population is created, genetic algorithm must determine the performance of each individual by using an adaptive function which assigns to each possible solution, a fitness value that reflects its quality. Fitness function must consider several criteria, such as distance, safety, smoothness etc. The definition of a suitable fitness function is a crucial task since genetic algorithm uses the information generated by this function to choose the individuals for reproduction, mutation, and at the end of the process, it selects the best solution in the final population according to its fitness value.

6.4. Selection Operator

Selection is a genetic operator used to choose parents likely to survive to produce the next generation. Parents with the best fitness values are more likely to be selected for mating. There are different selection methods that can be used: Elitism, Tournament, Roulette Wheel, Stochastic Universal Sampling, Linear Rank, Exponential Rank, and Truncation Selections. The main objective of the selection operator is promoting individuals with high adaptability to be selected for the next generation. The selection pressure is an important criterion which strongly influences the performance of genetic algorithm. Where selection pressure is high, genetic algorithm converges quickly without exploring every available search space. On the other hand, a low selection pressure produces random solutions. In our approach, Elitist and Truncation Selection methods are used to control the pressure selection. Elitist which has high pressure selection is used to keep the fittest solutions throughout generations, and Truncation Selection is used to create an avenue for weak chromosomes to be selected from the last generation for reproduction in the current one, and to avoid the dominance of the best individual [20].

6.5. Crossover Operator

After selecting individuals using the selection operator, the crossover is applied. Crossover is a genetic operator that blends the genetic information (genes) of two selected chromosomes (parents) to yield new chromosomes (offspring/child) for population heterogeneity, and to boost the fitness value of the candidate solutions. The main idea behind crossover is that new chromosomes inherit the best characteristic of their parents. Thus, the result is having a better child that performs better than its parents. The crossover rate is the probability of performing crossover. Different crossover operators have been introduced: the Partially-Mapped, the Order Crossover, the Cycle Crossover, and Same Point crossov-

er. Same point crossover seems to be the most used mechanism. Munemoto [21] in his work has used the standard crossover mechanism, same point crossover which holds two crossover strategies: the one-point and the two-point crossovers are applied if there are at least two identical genes between the parents. Same point crossover was applied because it provided a better solution than the rest.

6.6. Mutation Operator

Mutation is an intrinsic part of the genetic algorithm. It is a genetic operator applied to improve diversity and prevent premature convergence of algorithms. Generally, this operator randomly selects a position (gene) and replaces it with a new, non-existing gene on the path. Yet, as mentioned in Alajlan *et al.* [22], random mutations could generate invalid paths. Even if a solution is valid before the application of the mutation operator, the new gene altered can contain an obstacle and as well create an inappropriate path. In this study, we adopt random mutation. Mutation is performed by randomly choosing a cell from an individual and trying to replace same with one of its neighboring cells on the grid map. Figure 2 below depicts the algorithmic structure of the genetic algorithm and the pseudo-code is provided in the Appendix.

7. Discussion of Genetic Algorithm Result

The proposed GA has been applied for CHPED problem for 4 generating units. Cost function parameters along with feasible region coordinates of combined heat and power unit are taken from Tables 1-4 respectively. The system consists
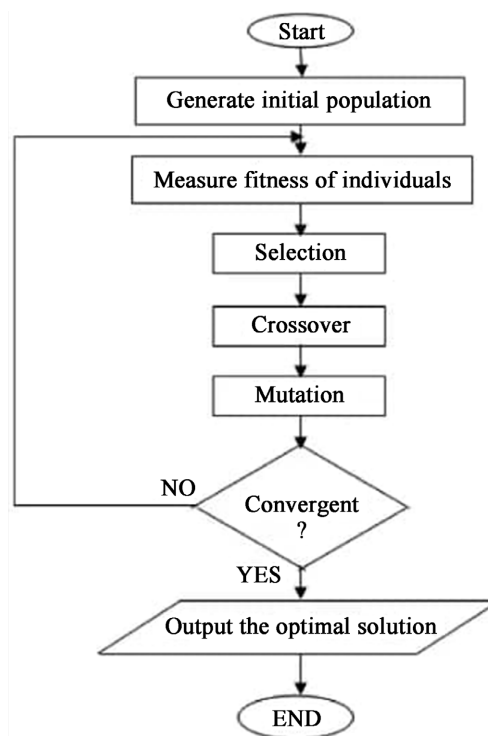
Figure 2. Flow chart of the GA-Based CHP optimization problem.

of two conventional power units: one cogeneration unit and a heat-only unit. The heat-power feasible operation region of the cogeneration unit is illustrated in **Figure 1**. As explained in the research paper, combined heat and power economic dispatch has been formulated with the objective of minimizing fuel cost. **Table 5** shows power generation and heat generation output result of four-unit test system with power demand P^D = 520 MW and heat demand Q^D = 300 MWh. The result in **Table 5** shows that using the above heat and power loads, only unit two reached its capacity limit when proposed algorithm was deployed to solve the combined heat and power economic dispatch problem and the minimum objective function value was obtained after 51 iterations, with cost function valueN21120.0. The obtained output decision variables (P_1, P_3, Q_3 and Q_4) were satisfactory for all the available constraints (equality and inequality constraints) associated with the combined heat and power economic dispatch problem in this research while output decision variable of unit 2 is infeasible. The global optimal solution obtained in this 4-unit test system, confirms the applicability of the proposed (genetic algorithm) for dealing with optimization problems of this class compared to existing techniques, improvements in the result are significant as shown with (particle swarm optimization and artificial bee colony algorithm). It is equally observed that the proposed genetic algorithm can converge to produce far reaching, diversified and extreme solutions due to its effective search capability. We therefore conclude that proposed algorithm provides a reasonable assessment of global solutions and better convergence speed. Genetic algorithm, being a probabilistic search technique, is known to be computationally more efficient for problems that permit probability solution similar to the one proposed in this research. **Figure 3** below depicts the combined heat and power output
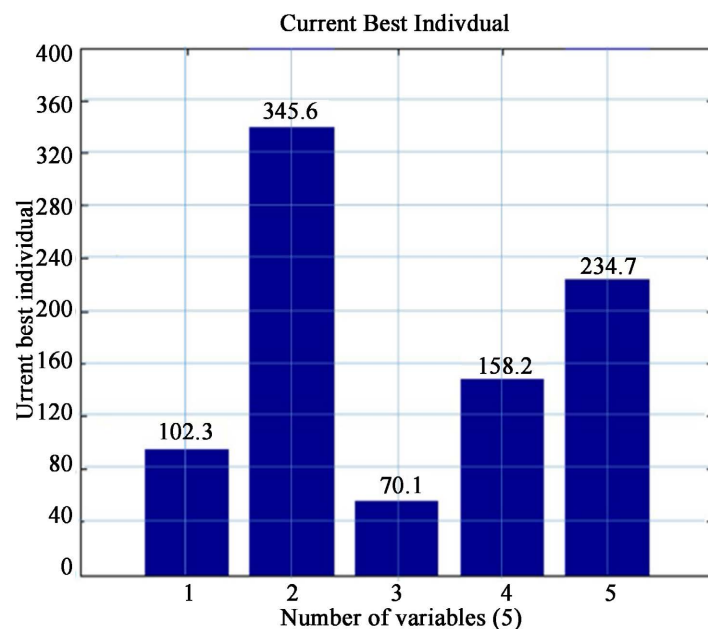

Figure 3. GA-Output with respective values of the independent variables.
$p_1 = 102.3, p_2 = 345.6, p_3 = 70.1, q_3 = 158.2, q_4 = 234.7$.

decision variables computed using genetic algorithm in the form of bar chart. Each bar represents an output decision variable (power or heat). Power and Heat Output decision variables of units 1, 3 and 4 operate within the required (feasible) bound, whereas unit-2 output decision variable is infeasible.

The result implies that simulated output decision variables—heat and power—at respective 520 MW and 300 MW loads have global minima on units 1, 3 and 4. They satisfy all available constraints, unlike unit 2 that could not find the optima in the specified maximum number of cycles. The proposed algorithm produced results quite close to the global optima with minimum objective function value.

The convergence characteristic of the proposed method for this case is depicted in **Figure 4**. It is observed that the proposed GA algorithm converges quickly in early iterations *i.e.* 51 lines and hence, the number of maximum runs can be decreased to save the solution time. Convergence of genetic algorithm is generally difficult to obtain due to the fact that evolutionary computations
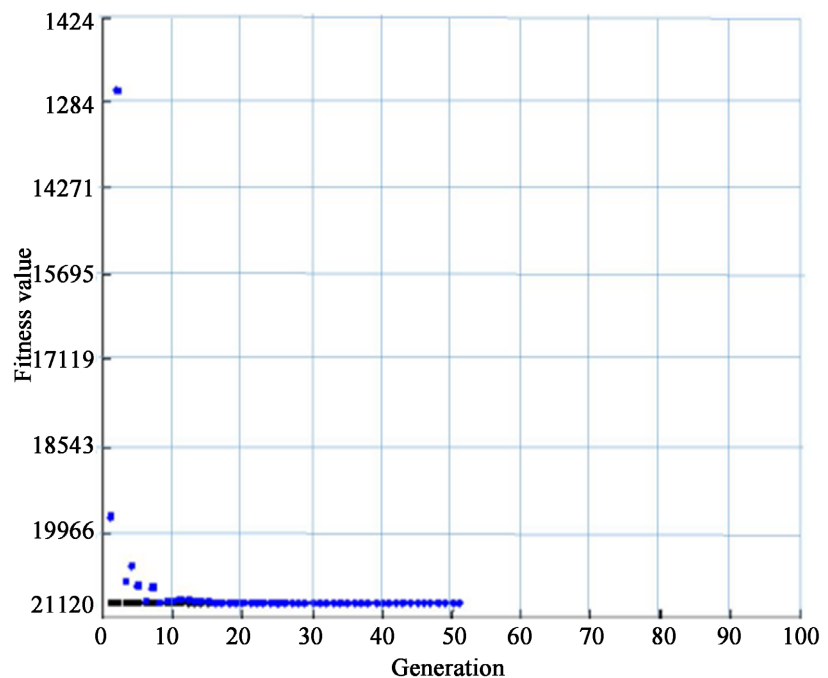
Figure 4. After 51 iterations we get minimum value of the fitness function; $z = 21,120$.

Table 5. Summary of results obtained from direct solution, genetic; particle swarm optimization algorithms.

	Direct solution (Lagrangian multiplier method)	Genetic Algorithm (GA)
P_1 (MW)	155.9	102.3
P_2 (MW)	169.1	345.6
P_3 (MW)	195.0	70.1
Q_3 (MWth)	120.0	158.2

incorporate complex nonlinear stochastic processes.

In comparison with the results obtained with the direct method [23], it appears reasonable to conclude that the proposed algorithm (GA) has good promise. However this result still needs to be compared with other meta-heuristic algorithms such as Particle Swarm Optimization and Artificial Bee Colony. This is subject for a future research paper.

8. Conclusion

A new perspective based on genetic algorithm was deployed in this paper for coherent solution of combined heat and power economic dispatch (CHPED) problem encountered in a simple cycle cogeneration system. Different attributes and constraints such as heat and power demands, feasible operation region of CHP units, and capacity limits of the units were taken into consideration in the formulation of combined heat and power economic dispatch (CHPED) problem. The efficacy of the GA was established using genetic algorithm codes. Our results have shown that GA can realize optimal solutions of the objective function value with good convergence characteristics. However, direct solution algorithm has less objective function but requires length recalculations when any of the units violates the constraints as experienced in unit three. Also, the effectiveness of direct solution algorithm when deployed in large units is not known. The formulation of the combined heat and power dispatch problem considered here is in conformity with the prevailing practice of using quadratic cost functions for the units. The possibility of extending genetic algorithm solution for cases where the cost function is not quadratic is currently being investigated.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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Appendix

The Pseudo-code for the Genetic Algorithm flowchart in **Figure 2** is given.

Input: N: Population size; P_c: Crossover rate; P_m: Mutation rate.

Output: Best Chromosome.

$$t \leftarrow 0$$

Initialize arbitrarily the initial population $P(t)$.

While (not termination condition) do

Evaluate $P(t)$ using a fitness function

Select $P(t)$ from $P(t-1)$

Recombine $P(t)$

Mutate $P(t)$

Evaluate $P(t)$

Replace $P(t-1)$ by $P(t)$

$$t \leftarrow t+1$$

End